Evolving Cellular Automata for Noise Reduction in Images

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ABSTRACT: A most common process in image analysis is noise reduction, with the objective of diminishing image components considered to be extraneous. This paper presents an Evolutionary Program that evolves image noise reduction procedures in form of dynamical rules for Cellular Automata. The method takes advantage of the pattern processing capabilities of Cellular Automata combined with the search power of Evolutionary Programs. The fitness function that guides the evolutionary search consists on a measure of the noise reduction quality obtained from the application of the Cellular Automata on a set of reference images conveniently contaminated with several levels of white noise. The method is applied both to simple monochromatic and 256 grayscale images, with different noise content, observing a performance comparable or better to that of traditional noise reduction methods. This work shows that the hybridization of Cellular Automata with Evolutionary Programs is a very promising approach for the implementation of general adaptive image processing tools.

Keywords: Evolutionary Programs, Cellular Automata, Restoration, Noise reduction, Noise Filtering, Image Processing, Emergent Computation.

1 INTRODUCTION

Noise reduction methods conform a very important branch of image processing closely related to image restoration, segmentation and border detection. They have been the object of extensive studies for their evident practical importance and also because of their theoretical interest. In short, noise reduction deals with techniques aimed at reducing the content of extraneous components (noise) in images that might have been contaminated by sensor operation, transmission, or by additive noise. The general approach to noise reduction in images consists on the design and application of particular filters both in space or frequency domains [1-5]. Space domain filtering methods are based on a convolution operation between the image and a suitable convolution kernel (mask). On the other hand, frequency domain filters use the Fourier transform to block and or attenuate certain spatial frequencies in order to reduce the undesired noise components. In the literature general methods for the construction of mask coefficients or frequency filters to encode a desired filter operation are described.

The proposed approach takes advantage of the capacity of Cellular Automata (CA) for generating and transforming a wide variety of patterns [6] to implement the computational task of noise reduction in images. Performing a computation with a CA means [7] that the input to the computation (noise degraded image) is encoded as the initial configuration, the output (filtered image) is decoded from the configuration reached by the dynamics some later time step. The intermediate dynamical steps, that transform the input to the output, are taken as the steps in the computation. The computation emerges from the CA rule being obeyed locally by each cell. Since it is very difficult to specify a priori the particular dynamical rule suitable for a desired computation an evolutionary process is applied in their search.

The method can be summarized as follows: An Evolutionary Program (EP), is applied in the search for adequate CA dynamical rules that perform noise reduction over a set of reference images with specific levels of noise contamination. The fitness function is a measure of quality of the filtering process that results from the application of the CA on the set of reference images. The evolutionary process starts from a random initial population of CA rules. The result is a set of evolved local transition rules defining a CA noise reduction filter, a device able to perform the task of filtering on any image with noise degradation similar to that of the reference set.

The organization of the paper is as follows: in section 2 an introduction to the applied methods of Emergent Computation is presented; in section 3, the proposed hybrid method of image noise reduction is described; in section 4 the experiments and results are discussed and, in section 5, the conclusions are presented.

2 METHODS OF EMERGENT COMPUTATION.

In the present work, the hybridization of two important methodologies of Emergent Computation, Cellular Automata and Evolutionary Programming is considered.

Cellular Automata (CA) were introduced by von Neumann and Ulam in the 1940s, to provide a formal framework to investigate the behavior of complex extended systems. They have been extensively studied as mathematical objects, as models of natural systems, and as architectures for fast, reliable parallel computation [6], [8], [10], their application as computational devices is not so widespread. A CA can be defined as a discrete dynamical systems: space, time and the state of the system are discrete. A CA consists of a regular grid of cells *(S)* in which each can be in one of k possible states belonging to a finite alphabet *(L)*. The configuration of the system at any time is defined as the set of state values $\{S_i\}$ of each cell [10]. The states are updated synchronously in discrete time steps according to a local, identical iteration rule. That is, a state of a cell at a given time depends only on its own state and the states of its nearby neighbors at the previous time step. This CA update dynamic is a mapping from all possible neighborhood configurations to the set of all states (S_i). This mapping defines the transition function *(T)* and can be considered as a table of all possibilities in a many-to-one relationship. The number ν and location of the neighboring cells considered in the transition function define the neighborhood (V). A Cellular Automata can then be defined by the four-tuple:

$$AC = \{S, L, V, T\} \tag{1}$$

with the transition function written as:

$$\boldsymbol{T} : \boldsymbol{L}^{\nu} \rightarrow \boldsymbol{L} \Rightarrow (s_1, s_2, ..., s_\nu) \in \boldsymbol{L}^{\nu} \rightarrow \boldsymbol{T}(s_1, s_2, ..., s_\nu) \in \boldsymbol{L} \tag{2}$$

that is:

$$s_i(t+1) = T(s_1(t), ..., s_\nu(t)) \quad \forall\, s_i \in S \tag{3}$$

The dimensionality of the cellular space S, the number k of allowed states and the size of the neighborhood ν depend on the problem at hand. The main difficulty lies in the specification of an adequate transition function that defines a CA-dynamic able to perform a desired computational task. This problem is greatly enhanced due to the exponential dependence of the number of possible transition functions on k and ν. This difficulty is tackled by the application of an evolutionary program.

Evolutionary Programs [11,12] implement stochastic search methods that mimic the metaphor of natural biological evolution. EP operate on a population of potential solutions applying the principle of survival of the fittest to produce better and better approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation. In EP natural processes, such as selection, recombination, mutation, migration, locality and neighborhood are modeled. Since EP work on populations of individuals instead of single solutions the search is very efficient and is performed in a parallel manner.

3 EVOLVIG CELLULAR AUTOMATA FOR NOISE REDUCTION.

The proposed method consists in the evolution of CA specifications capable of performing noise reduction, in short in the evolution of a CA noise filter. The computation proceeds by initializing the CA configuration with the image to be restored and iterating the local dynamical rules to obtain as end configuration of the CA the restored image. The cellular space S of a two dimensional CA is a convenient structure to represent a digital image with the state of each cell holding information of the color for the pixel in that specific position. The size of S and the cardinality of the alphabet L depends on the image considered, $k = 2$ for monochromatic images, $k = 16$ for 16 colors, and so on. The generalization to images of other color models, e.g. RGB, is obvious.

The individuals I_i in the EP encode a complete definition of a CA filter, they are represented as a data structure of the form:

$$I_i = \{S, L, V_i, T_i\} \tag{4}$$

the size of S and L are constant and depend on the type of images. Six types of neighborhoods are considered, von Neumann, Moore and a mixed version of them including first and second nearest neighbors.

In the initialization of the individuals the neighborhood V_i is randomly selected with an a priori probability and is then held constant. The set of transition rules T_i is randomly initialized, both the cardinality of the set and the definition of each transition rule is chosen at random. The definition of each rule is coherent with the alphabet L and selected neighborhood V_i, the structure is that of a (v+1)-tuple of values belonging to alphabet L:

$$T = \{(c_1, c_2, ..., c_v, c_{v+1}) \ \forall c_i \in L\} \tag{5}$$

The first v elements correspond to the neighborhood configuration at time t and the (v +1) to the state of the central cell at time $t+1$. If a neighborhood configuration does not unify with the antecedents (s_1, s_2, ..., s_v) of any rule it is assumed, in that time step, that the central cell remains in its actual state. In the definition of the rule set care must be taken to exclude redundancies and inconsistencies. It is considered that the rules are invariant under the symmetry operations of the selected neighborhood. In order to reduce the number of possible rules the following two considerations are made: First, the possible incorporation of wild cards and Second, for images of greater color content a similarity range in the unification procedure of the rule. The initial inclusion of wild cards follows an a priori probability distribution and the similarity range is a parameter setting made through trial and error.

The following evolution operators of crossover and mutation types were randomly applied on roulette wheel selected parents [11,12]:

- One point crossover of the rule set for individuals with the same neighborhood.
- Random crossover of the rule set for individuals with the same neighborhood.
- Addition of a random generated rule to the rule set of an individual.
- Random deletion of a rule from the rule set of an individual.
- Alteration of the conclusion of a random selected rule from the rule set of an i n-dividual.

In the evolution, a fraction of the best individuals of the parent population survive into the following generation. The population is completed with evolved offspring and the worst individual is replaced by a new randomly generated individual.

The fitness is calculated by measuring the noise reduction quality of the CA filter it encodes. This quality figure is calculated from the average similarity measure between the output of the CA filter and the original noiseless image over a reference set of images. The reference set is previously chosen and include noiseless and with a certain level of white noise contaminated images. The fitness function is defined by:

$$f(I_i) = \left(\sum_{i=1}^{N} \xi_i \Big/ N \right)^{-1} \tag{6}$$

In this expression ξ_i is the similarity between the output image from the CA filter and the corresponding noiseless images: the Hamming distance for monochromatic images ($L = 2$) or a quadratic error measure when $L > 2$. N is the number of images in the reference set. Since the original images are included in the reference the fitness function incorporates terms that penalizes negative perturbations of the CA filter over the original noiseless images.

4 EXPERIMENTAL RESULTS

The proposed method is applied to the noise reduction of monochromatic and grayscale images. To this end, two experiments were performed with the following parameter settings for the evolutionary program established by trial and error.

- Population size: 20;
- Percentage of the population surviving in the next generation: 10%;
- Probability for Crossover type operators: 0.85;
- Probability for Mutation type operators: 0.15.

A priori probabilities for the inclusion of the types of neighborhoods and of wild cards in the initial individuals:

- $p_1 = 0.26$ (*von Neumann* first nearest neighbor);
- $p_2 = 0.18$ (*von Neumann* second nearest neighbor);
- $p_3 = 0.18$ (*Moore* first nearest neighbor);
- $p_4 = 0.10$ (*Moore* second nearest neighbor);
- $p_5 = 0.18$ (*Mixed* first nearest neighbor);
- $p_6 = 0.10$ (*Mixed* second nearest neighbor);
- $p_{WC} = 0.15$ probability inclusion of wild card;

In the evaluation of the individuals it was assumed, for convenience, that the CA computation was performed in one dynamical step. Nevertheless, a CA filter can be applied successively several times. As stopping criteria, a maximum of 100 iterations of the EP was used.

In order to describe the quality of the results it would be ideal if an evaluation criterion or performance measure corresponding to either the human visual system or the requirements of the subsequent processing steps were available. Since unfortunately, such criteria are difficult to find, in this section a simple approach is adopted: the percentage of pixels of the filtered image equal or similar to those in the original image is defined as the noise reduction quality $\delta(\varphi_i)$.

$$\delta(\varphi_i) = \tilde{A}\,\Gamma * 100 / \hat{O};\quad \Gamma\tilde{A}* = \sum_{i=1}^{S} \theta\left(\left|s_i^o - s_i^r\right|, \mu\right); \qquad (7)$$

$$\theta(x, y) = \begin{cases} 1, & x \le y \\ 0, & x > y \end{cases}$$

where $\Gamma\Gamma*$ is the number of equal or similar pixels, $\boldsymbol{T}$ the total number of pixels and μ is the similarity range.

4.1 First Experiment.

Three monochromatic images of 130 x 130 pixels were used as reference images (see figure 1), each was contaminated with white noise at levels of 10%, 20% and 30%. The evolutionary program was then independently applied, in the evolution of three one step CA filters for the corresponding noise contamination level. .

In Figure 1 the results obtained after the successive application of the three CA filters (in the order 30%, 20% and 10%), over a 30% contaminated image can be appreciated. The measures of quality obtained in these experiments are of 92.57, 98.25 and 92.30 percent respectively.

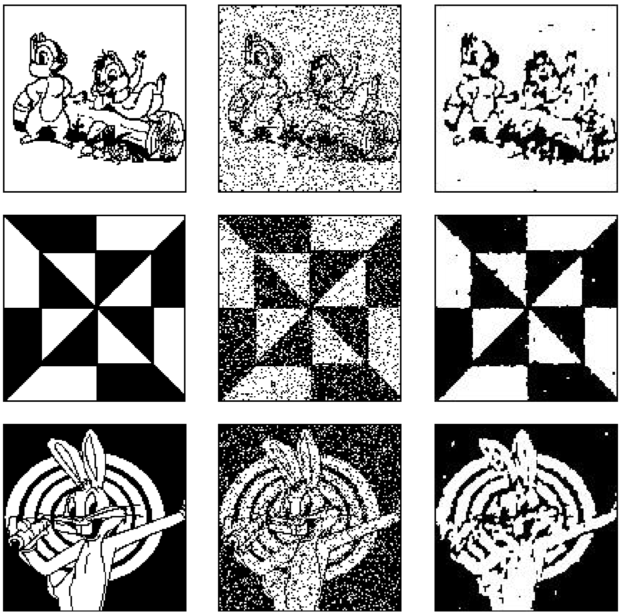

Figure 1. Original images (left), 30% white noise contaminated (center) and restored by the successive application of the CA filters evolved with 30%, 20% and 10 % contaminated reference images (right).

Figure 2 shows the result of the application of the same three CA filters to the orig i-nal noiseless images. These resulting images have quality measures of 95.95, 99.92 and 96,38 percent respectively.

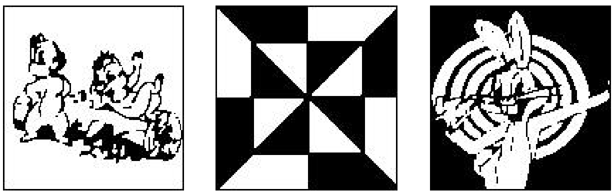

Figure 2. Effect of the application of the three CA filters on the original noiseless images.

In table I the noise reduction quality resulting from the successive application of the three CA filters (in the order 30%-20%-10%) to images with noise contamination levels between 0% and 40% are presented. It can be appreciated that the effect of CA filters evolved with high noise contamination to images with lower level of noise deteriorates the quality of the filter.

Table I. Noise Reduction quality for 10%, 20%, 30% CA filters.

Image	0 %	10 %	20 %	30 %	40 %
A	95.95	95.21	93.95	92.57	91.36
B	99.92	99.46	99.04	98.25	96.56
C	96.38	95.09	94.33	92.30	91.05

In another approach a CA filter evolved using low level noise images (10%) is repeatedly applied over the contaminated images. The resulting noise reduction quality is shown in table 2.

Table II. Noise Reduction quality after the successive application of 10% of CA filters.

Image	0 %	10 %	20 %	30 %	40 %
A	98.41	97.15	95.65	93.59	89.64
B	99.98	99.43	98.62	97.25	93.69
C	98.49	97.46	95.22	92.93	89.76

4.2 Second Experiment.

In this experiment grayscale images were considered. This case is more complicated than the former one, not only is the alphabet of the CA of greater cardinality (*L=256*) but the visual quality of the images to be filtered depend on more attributes (brilliance, shade, luminance, etc.). In the experimentation two 210 x 210 pixel images, extracted from the work of Geman and Geman [14], are used as references (Figure 3).

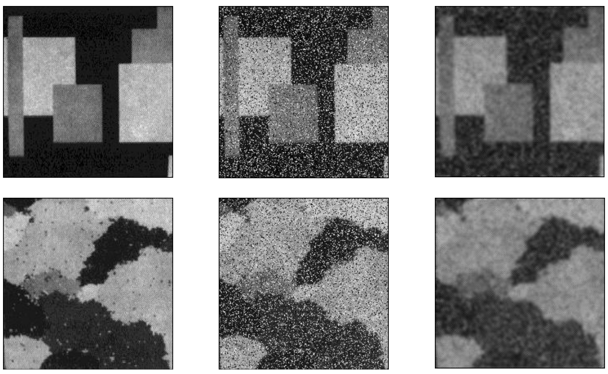

Figure 3. Original noiseless images (left), 30 % white noise contaminated (center) and restored (right) after the successive application of the three CA filters of 30, 20 and 10 %.

In this case a similarity threshold of 15 discrete levels is set. Three CA filters, corresponding to reference noise contamination levels of 10%, 20% and 30% were evolved. Figure 3 shows the case of successively applying the three CA filters to the image contaminated at a level of 30%. The resulting quality is 33.02 and 34.21 percent respectively.

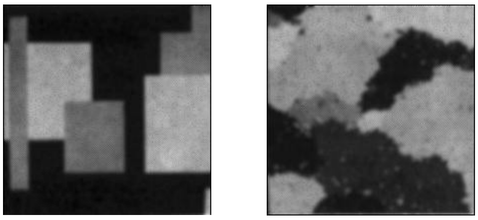

Figure 4. Result of the successive application of the three CA filters to the original noiseless images.

In figure 4 the results of the application of the three CA filters on the original noiseless images are shown. The filters produce a slight blurring of the images with qualities of 64.48 and 59.10 percent respectively.

When the 10% CA filter is applied three successive times the quality measures are better: 43.90 and 41.71 percent on the 30% contaminated images and 67.16 y 65.10 percent on the original noiseless images.

In figure 5 the results of the application of the 30% CA filter on a 30% noise contaminated image of Lena can be appreciated.

Figure 5. Application of the 30 % CA filter on the Lena image.

From left to right figure 5 shows the original noiseless Lena image, a 30% noise level contaminated image, the filtered result with a quality of 46.67 percent and the resulting image after the application of the CA filter to the original image. (82.33 quality).

These results on grayscale images are very promising since the visual validation render them comparable with results reported in the literature [13]. In this experiment the concepts of wild card and similarity range come out very useful in the simplification of the evolved rule set for the CA filters.

The price to pay for this simplification is the diminished quality of the restored im a-ge in particular in regard to their brilliance and luminance. Nevertheless the forms and objects in the image are widely conserved.

5 CONCLUSIONS AND DISCUSSION

A novel Cellular Automata based, image noise reduction method has been proposed. The method applies an Evolutionary Program in the search of a particular set of transition rules through which a Cellular Automata performs the computational task. The performance of the Evolutionary Cellular Automata in the task of noise reduction is comparable to those found in existing methodologies. The most striking difference between the proposed method and those reported in the literature is that the Cellular Automata performs an emergent computation. That is, the global computation is performed through the synchronous application of local transition rules.

Even when the proposed noise reduction technique is still in experimental and test phases, the results of the experiments show that it is a very promising approach. However, many improvements are still needed in the methodology, in particular those leading to the achievement of better settings for the parameters of the Evolutionary Program, the selection of adequate reference images and the definition of other forms for the implementation of the Cellular Automata dynamics. The method needs also to be generalized to much more widespread information, such as images of different types, colors and sizes.

Finally it must be noted that the idea of using a hybrid method that combines the pattern transformation capabilities of the Cellular Automata with the search power of the Evolutionary Programs is very promising as a tool for solving complex and not well defined computational tasks. On one side the Cellular Automata perform intrinsic parallel processing with possibilities of hardware implementations. On the other the Evolutionary Program provides a general methodology for the difficult task of obtaining the adequate set of transitions rules that defines the computational dynamic of the Cellular Automata.

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